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Unsupervised Pedestrian Detection in Still Images

by Prudhvi Gurram, Shuowen Hu, Christopher Reale, and Alex Chan

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14. ABSTRACT

In this report, an unsupervised pedestrian detection algorithm is proposed. An input image is first divided into overlapping detection windows in a sliding fashion and histogram of oriented gradients (HOG) features are collected over each window using non-overlapping cells. A distance metric is used to determine the distance between histograms of corresponding cells in each detection window and the average pedestrian HOG template (determined a priori). The distance feature vectors over overlapping blocks of cells are concatenated to form the distance feature vector of a detection window. Each window provides a data sample that is extracted from the whole image and then modeled as a normalcy class using support vector data description (SVDD). Assuming that most of the image is covered by background, the outliers that are detected during the modeling of the normalcy class can be hypothesized as detection windows that contain pedestrians in them. The detections are obtained at different scales in order to account for the different sizes of pedestrians. The final pedestrian detections are generated by applying non-maximal suppression on all the detections at all scales. The system is tested on the INRIA pedestrian dataset and its performance analyzed with respect to accuracy and detection rate.

15. SUBJECT TERMS

Pedestrian detection, anomaly detection, support vector data description, unsupervised learning

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1. Introduction

Pedestrian detection is an important research area in machine vision due to its impact on wide-ranging applications like robotics, surveillance, and vehicular technology for the military, the law enforcement community, and the commercial sectors. For the military, recent conflicts in dense urban settings have heightened the need for robust human detection (referred to as dismount detection) in cluttered scenes. For the automotive industry, automatic indication and avoidance of pedestrians using onboard sensors and processing has become an important safety feature for luxury vehicles. For the law enforcement community, the widespread adoption of low-cost and readily available surveillance systems have created a deluge of data, far beyond the capacity of existing personnel to monitor. Hence, there are diverse and urgent needs to develop automated pedestrian detection systems.

One of the early seminal works in object detection is the cascade of classifiers approach developed by Viola and Jones in 2001 (*1*). Viola and Jones (*1*) used simple but computationally efficient rectangle features to train a cascade of classifiers for detecting objects, with face detection being an example application described by the paper. They also introduced the integral image, which enabled quicker computations of the rectangle features. In 2005, Dalal and Triggs (*2*) developed a feature for object detection called histogram of oriented gradients (HOG), in which the histograms of edge orientations are collated across cells and concatenated across densely overlapping blocks. HOG features have proven to be extremely effective for human detection and face detection, even with a linear support vector machine (SVM) classifier, as demonstrated by Dalal and Triggs. Since then, many works in human/pedestrian detection have been published in literature, some of which focused on optimization and reducing runtimes, while others focused on developing novel features and classifier designs. Dollar et al. (*3*) recently reviewed the state-of-the-art algorithms for pedestrian detection, and also provided a summary of the databases available for algorithm development. Dollar et al. concluded that almost all modern detectors use some version of gradient histograms, with the best detectors utilizing a combination of features. Among all the techniques evaluated in Dollar's review paper, the Fastest Pedestrian Detector in the West (*4*) had the best performance when both runtime and detection rate were taken into consideration. However, detection of small-scale humans remained highly problematic even for the state-of-the-art algorithms.

Furthermore, all the existing techniques for pedestrian detection are supervised algorithms, to the best of our knowledge. The general framework of such algorithms consists of extracting low-level features like HOG features in the first step, and collecting and labeling these features according to a template (full human or parts of a human) to form training samples. These samples are extracted from positive (human present) and negative (human not present) images, and used to train a binary classifier. There have been numerous efforts to improve the

performance of pedestrian detectors in terms of speed by using a cascade of classifiers framework, and in terms of accuracy, by using additional features. Supervised pedestrian detectors suffer from the disadvantage that the test data distributions should be similar to the training data distributions, and these detectors will fail if there is a substantial change in the scene or scale of the pedestrians. In typical military operational environments, unfortunately, scene changes could be frequent and rapid. In addition, training data from different field conditions may not be readily available to train/customize supervised algorithms, therefore, necessitating the need to develop unsupervised human detection methods.

In this report, we propose an unsupervised pedestrian detection algorithm to address the challenges related to training data scarcity and testing data variability. Given an input image, the proposed technique extracts HOG feature from a sliding window and computes a distance metric with respect to an average pedestrian HOG template for each window. The distance metrics from all the windows across the image form a collection of data samples, which is used by support vector data description (SVDD) to generate a normalcy class, while allowing a percentage of the data samples to be outliers. In typical imagery, the majority of the scene is composed of non-human objects; therefore, the resulting normalcy class would be non-human (i.e., background), while windows containing humans tend to be the outliers (i.e., detections). An input image is processed at multiple scales using the proposed unsupervised technique by resizing the input image. Subsequently, detections at all scales are aggregated into final detection boxes through non-maximal suppression. This report is organized as follows: section 2 describes the principles of SVDD, section 3 explains each stage of the proposed approach, and section 4 presents experimental results, followed by the conclusion in section 5.

2. Support Vector Data Description

SVDD is a kernel-based anomaly detection technique (*5*) that characterizes the normalcy data set in a high-dimensional feature space induced by a kernel function, such as Gaussian radial basis function (RBF) kernel. SVDD obtains an optimal hypersphere that includes only the relevant normalcy data and excludes the superfluous space around the dataset. The boundary of the enclosing hypersphere is defined by the vectors or samples in the normalcy data, which are called support vectors. The enclosing hypersphere serves as a decision boundary to test if new data points belong to the normalcy pattern. The data samples that lie outside this boundary are detected as outliers or anomalies. Consider a data set containing samples represented as $\{\boldsymbol{x}_i\}$, where $\boldsymbol{x}_i \in \mathbb{R}^d$ is a d-dimensional feature vector of each data sample i. After transformation to the high-dimensional space, the data samples are represented as $\boldsymbol{\Phi}(\boldsymbol{x}_i)$, where $\boldsymbol{\Phi}$ is the function that transforms the input feature vector to a high-dimensional (possibly infinite) reproducing kernel Hilbert space (RKHS). The SVDD algorithm tries to find the smallest hypersphere in this space that encloses the given normalcy data set in order to exclude the superfluous space around

the background data set as much as possible. This sphere is defined by its center $\boldsymbol{a}$ and radius R. If there is a possibility of outliers existing in the data, then the optimization problem is expressed as shown in equation 1 with the help of slack variables to allow for the outliers.

$$\begin{aligned} &\min L(\boldsymbol{a}, R) = R^2 + C \sum_i \xi_i \\ &\text{subject to } \|\boldsymbol{\Phi}(\boldsymbol{x}_i) - \boldsymbol{a}\|^2 \leq R^2 + \xi_i,\ \forall\, i = 1, 2, \dots, n, \\ &\xi_i \geq 0, \forall\, i = 1, 2, \dots, n, \end{aligned} \tag{1}$$

where parameter C controls the trade-off between the volume of the hypersphere and the percentage of errors. After applying Lagrange multipliers $\{\alpha_i\ , i\ =\ 1, 2, \dots, n\}$ and the Karush-Kuhn-Tucker (KKT) conditions (*6*), the dual problem is given by

$$\begin{aligned} &\min L(\alpha_i) = \sum_{i,j} \alpha_i \alpha_j \langle \boldsymbol{\Phi}(\boldsymbol{x}_i), \boldsymbol{\Phi}(\boldsymbol{x}_j) \rangle - \sum_i \alpha_i \langle \boldsymbol{\Phi}(\boldsymbol{x}_i), \Phi(\boldsymbol{x}_i) \rangle \\ &\text{subject to } 0 \leq \alpha_i \leq C, \forall\, i = 1, 2, \dots, n, \textstyle\sum_i \alpha_i = 1 \end{aligned} \tag{2}$$

Since we do not know the explicit transformation function, it is performed using a kernel trick. The kernel trick is described as representing the dot product of transformed feature vectors (in high-dimensional space) with the help of a kernel function associated with the corresponding RKHS as shown in equation 3.

$$k(\boldsymbol{x}_i, \boldsymbol{x}_j) = \langle \boldsymbol{\Phi}(\boldsymbol{x}_i), \boldsymbol{\Phi}(\boldsymbol{x}_j) \rangle \tag{3}$$

Using this trick, the dual form of the optimization problem can be derived as

$$\begin{aligned} &\min L(\alpha_i) = \sum_{i,j} \alpha_i \alpha_j k(\boldsymbol{x}_i, \boldsymbol{x}_j) - \sum_i \alpha_i k(\boldsymbol{x}_i, \boldsymbol{x}_i) \\ &\text{subject to } 0 \leq \alpha_i \leq C, \forall\, i = 1, 2, \dots, n, \textstyle\sum_i \alpha_i = 1 \end{aligned} \tag{4}$$

This is a convex quadratic programming problem for any kernel that satisfies Mercer's theorem (*7*) and can be easily solved to obtain the optimal Lagrangian multipliers $\{\alpha^*\}$. The center of the hypersphere, which cannot be determined explicitly, is given by

$$\boldsymbol{a} = \textstyle\sum_i \alpha_i^* \boldsymbol{\Phi}(\boldsymbol{x}_i) \tag{5}$$

The vectors with $\alpha^* = 0$ lie inside the hypersphere and are considered to be part of the background data. The vectors with the corresponding Lagrange multipliers $0 < \alpha^* < C$ are the support vectors that actually lie on the boundary of the hypersphere. The vectors that have the corresponding Lagrange multipliers $\alpha^* = C$ are the outliers (still support vectors) that are allowed by the introduction of slack variables. These vectors lie outside the hypersphere. The radius of the hypersphere is given by

$$R^2 = \frac{1}{N_b}\sum_{k=1}^{N_b}\{\|\boldsymbol{\Phi}(\boldsymbol{x}_k) - \boldsymbol{a}\|^2\}$$

$$= \frac{1}{N_b}\sum_{k=1}^{N_b}\{k(\boldsymbol{x}_k, \boldsymbol{x}_k) - 2\sum_i \alpha_i^* k(\boldsymbol{x}_k, \boldsymbol{x}_j) + \sum_{i,j} \alpha_i^* \alpha_j^* k(\boldsymbol{x}_i, \boldsymbol{x}_j)\}, \quad (6)$$

where $\boldsymbol{\Phi}(\boldsymbol{x}_k)$, $k = 1, 2, \ldots, N_b$ are the support vectors that lie on the boundary of the background data set, and N_b is the total number of support vectors. When Gaussian RBF kernel is used with this algorithm, the SVDD method is similar to non-SVM based one-class classifier described by Scholkopf and Smola (*8*). The test statistic of SVDD can then be expressed as

$$F_{SVDD}(\boldsymbol{x}_T) = k(\boldsymbol{x}_T, \boldsymbol{x}_T) - 2\sum_i \alpha_i^* k(\boldsymbol{x}_T, \boldsymbol{x}_j) + \sum_{i,j} \alpha_i^* \alpha_j^* k(\boldsymbol{x}_i, \boldsymbol{x}_j) \geq R^2. \quad (7)$$

The test statistic $F_{SVDD}(\boldsymbol{x}_T)$ basically represents the distance between the outlier $\boldsymbol{x}_T$ (the data sample with a Lagrange multiplier $\alpha^* = C$) and the center of the hypersphere. This distance generates a confidence level with which a data sample can be considered to be an anomaly.

An important parameter that has to be considered in the present work is C, the trade-off parameter between the volume of the hypersphere and the number of outliers allowed. As explained by Scholkopf and Smola (*8*), C can also be expressed as $1/(\nu \times N)$, where ν represents the upper bound on the outliers permissible and also represents lower bound on the number of support vectors that determine the boundary of the hypersphere, and N is total number of samples in the data set. The parameter ν can be varied based on the maximum number of outliers being expected in a certain dataset.

---

3. Pedestrian Detection Using SVDD

In this report, we use the SVDD technique described in the previous section in order to perform pedestrian detection in images. First of all, HOG-based features are extracted from overlapping windows in an image. Each detection window forms a data sample that is used in the modeling of the normalcy class. The permissible outliers during the modeling stage are presumably the detection windows containing pedestrians, since the majority of the image consists of background pixels. The confidence score of each detected outlier is given by a normalized version of the SVDD statistic shown in equation 7. This process is repeated at different scales of the image to account for potentially different sizes of the pedestrians in the image. Non-maximal suppression is performed on all preliminary detections at various scales and selected the final detection window based on its confidence score. The block diagram of the algorithm is illustrated in figure 1. Each of the major steps in the algorithm is further explained in this section.

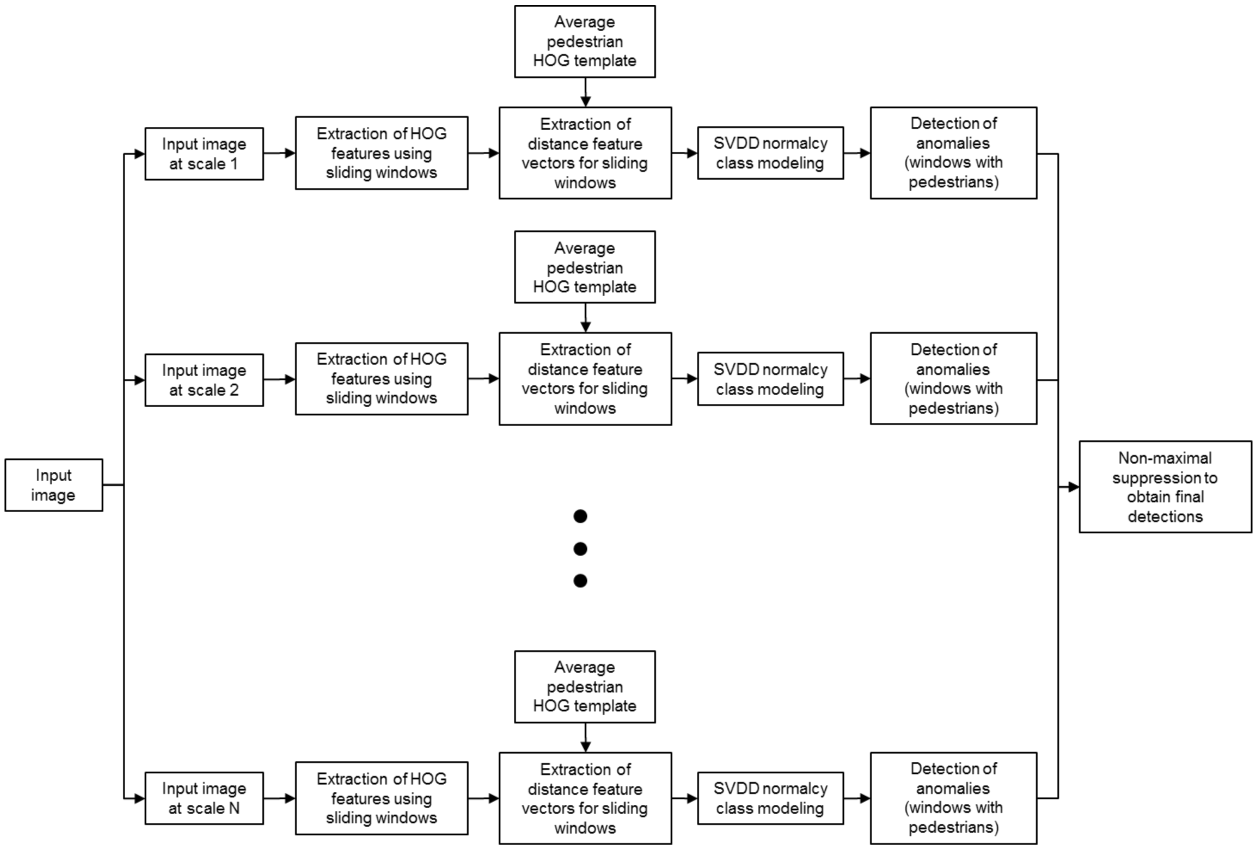


Figure 1. Block diagram of pedestrian detection using SVDD.

3.1 HOG-Based Pedestrian Detector

First, we give a brief description of the Dalal and Triggs algorithm (*2*) as we use HOG-based features in this work. Each detection window of size 64×128 is divided into cells of 8×8 pixels. The gradient information is quantified in each cell into a 9-bin histogram of oriented gradients. Then, the 3×3 cells are integrated to form a 9-cell block. More blocks are formed in a sliding fashion and the number of blocks per detection window depends on the number of pixels being skipped to form the next block. In this report, the blocks are formed with a sliding factor of 8 pixels. The 9-bin HOG features over 9 cells are concatenated to form an 81-dimensional feature vector for each block. A 64×128 window has $6 \times 14 = 84$ blocks. The 81-dimensional feature vectors of 84 blocks are in turn concatenated to form the 6804 feature vector for each detection window. These features are then input into a linear SVM to perform pedestrian detection (*2*).

3.2 Image Scaling

As explained in the previous subsection, the HOG features are extracted from an image over sliding detection windows of 64×128 pixels in size. However, if the size of the pedestrians in an input image is much larger than this window size and our algorithm is applied on the original

input image, it will not be able to detect these pedestrians. One of the options to deal with this issue is to increase the size of the sliding detection windows. By doing so, however, there is a need to determine and store the average pedestrian HOG template of different sizes. Alternatively, the input image can be scaled to different sizes while keeping the size of the detection window the same, which is equivalent to increasing the size of the detection window while keeping the original size of the input image. This scaling effect is illustrated in figure 2. The image scaling is performed to successfully detect pedestrians of different sizes in the input image.

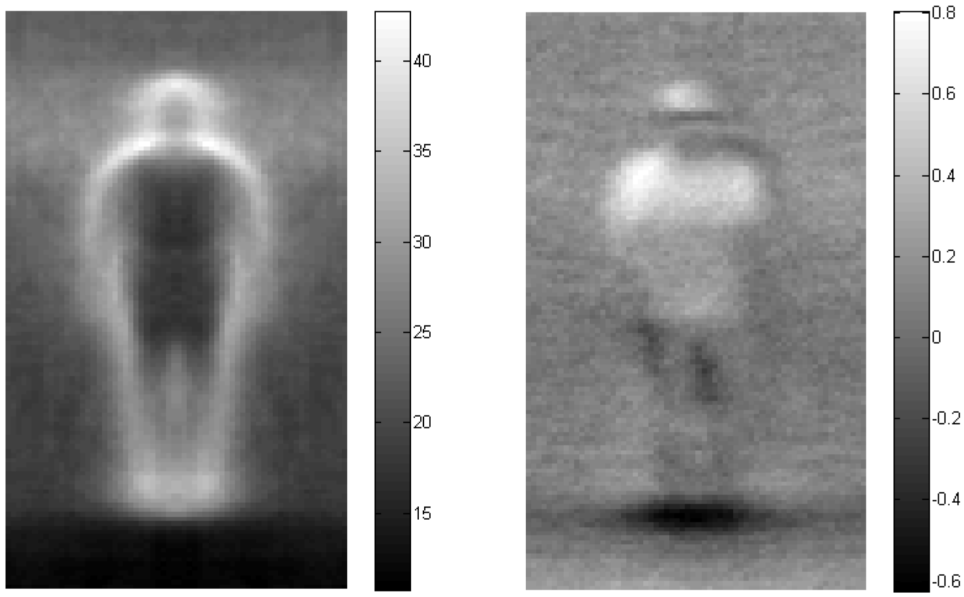
(a) Downsampling the image, size of detection window remains same

(b) Size of the image remains same, scaling up the size of detection window

Figure 2. Image scaling and window scaling.

3.3 Average Pedestrian HOG Template

Similar to the work of Dalal and Triggs (*2*), our HOG features are generated for overlapping detection windows and used to build the normalcy class. In some settings, there are objects that look like neither pedestrians nor background, hence are detected as anomalies as well. So, in order to set a spatial constraint on how the normalcy class looks like and what the possible anomalies look like, we use prior information about the pedestrians. The 2416 positive training detection windows from the INRIA dataset (*9*) are taken and HOG features are calculated over cells of 8×8 pixels. Each window consists of 8×16 cells with 9-bin feature vector for each cell. These HOG feature windows are averaged over all the positive training windows to obtain a single average pedestrian HOG feature template with the size of $8 \times 16 \times 9$. This is the only prior information that is finally used in our algorithm. The average gradient information (magnitude and phase) over all the pedestrian training windows is shown in figure 3.



(a) Average Magnitude of the Gradient (b) Average Phase of the Gradient

Figure 3. Average gradient information for pedestrians.

3.4 Feature Extraction

In this work, each input image is divided into overlapping detection windows in a sliding fashion. Similar to the original supervised method of HOG pedestrian detector, each detection window is sized to be 64×128 pixels. The stride of the sliding window is set to 8 pixels so that the HOG features need not be calculated repeatedly for each window, but the entire image can be divided into cells of 8×8 pixels and HOG features can be calculated for only one time. After this, all the cells belonging to a detection window are simply grouped together to obtain the HOG features corresponding to that window. For any detection window, distances between the histograms in corresponding cells of the average pedestrian HOG template and each detection window of the input image are calculated using the distance metric shown in equation 8.

$$h_d(i,j) = \left| h_{template}^{p_{ij}}(i,j) - h_{detwin}^{p_{ij}}(i,j) \right| \tag{8}$$

Here, h_d represents the distance feature of each cell in the window with indices (i,j), $h_{template}$ represents the histogram of a cell from the average pedestrian HOG template, and h_{detwin} is the histogram of the cell from the detection window. Variable p represents one of the 9 orientation bin numbers at which the maximum of the histogram of the cell from the average pedestrian HOG template occurs. It is computed according to equation 9:

$$p_{ij} = \arg\max h_{template}(i,j) \tag{9}$$

Since each detection window has 8×16 cells, we are left with 8×16 distance features. Similar to the original HOG-based pedestrian detector, these distance features over 3×3 cells are concatenated to form a feature vector corresponding to each block with a vector dimension of 9.

The 9-dimensional feature vectors of 84 blocks in each window are then concatenated to form a 756 distance feature vector for each detection window.

3.5 SVDD Modeling

At each scale of the input image, the feature vectors from all the windows constitute the data samples. These samples are used in equation 1 to model the image at a particular scale as a normalcy class, while allowing certain percentage of the data samples to be outliers by setting the value of ν (see section 2). Thus, all the samples that have no resemblance to pedestrians would have similar distribution of the feature vectors and would form the normalcy class. This is due to the fact that these samples make up the majority of the image. All the samples that resemble the pedestrian HOG template will be modeled as outliers since the feature vectors of these samples would be significantly different from the normalcy class.

As shown in figure 1, the SVDD modeling is performed on the input image at different scales in order to account for the different sizes of the pedestrians. The anomalies or outliers detected during the modeling process represent the windows containing pedestrians in them. Usually, each pedestrian in the input image results in multiple detections due to two reasons—the HOG features extracted from overlapping neighboring windows at a particular scale are very similar to one another and the HOG features extracted from windows at successive scales of input image are similar to one another. In order to merge these duplicated detections into a final detection, a step called non-maximal suppression (NMS) is applied on the detections obtained at different scales, as shown in figure 1.

The confidence level or score of each detection is needed to perform NMS. In this algorithm, the SVDD test statistic shown in equation 7 is used to generate the confidence scores of the outliers. The scores are the distances between the centers of the enclosing hyperspheres and the anomalies obtained at different scales of the input image. The radii of the enclosing hyperspheres that are modeled at various scales are different, and hence, the scores from equation 7 cannot be directly compared to each other. To deal with this problem, the scores are normalized by the radii of the hyperspheres at respective scales, as shown in equation 10. These scores represent the confidence level of the detections with respect to the unit enclosing hypersphere and can be used for NMS.

$$Con(x_T) = \frac{k(x_T,x_T) - 2\sum_i \alpha_i^* k(x_T,x_j) + \sum_{i,j} \alpha_i^* \alpha_j^* k(x_i,x_j)}{R^2} \quad (10)$$

3.6 Non-Maximal Suppression

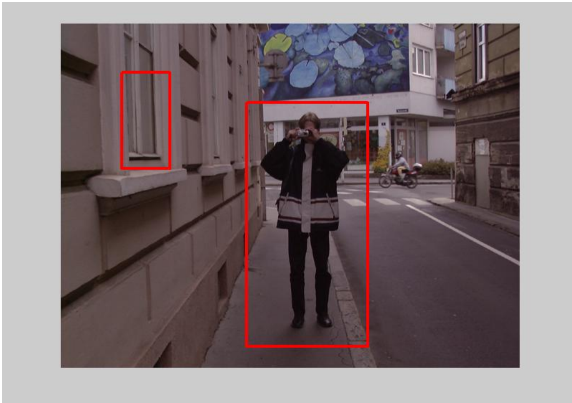
The final stage of the proposed unsupervised technique is NMS, which aggregates the detections at all scales from SVDD into final detection boxes. Two NMS techniques are commonly employed by pedestrian detection algorithms: mean shift mode estimation (*2*) and pairwise max suppression (*10*). The mean shift method for NMS has multiple parameters to be determined, while the pairwise max suppression has only one adjustable parameter and is very

computationally efficient. In this work, we used the modified pairwise max suppression described in the addendum of the integral channel features paper by Dollar et al. (*11*). For a pair of detection boxes, define a ratio as the area of the intersection between the two detection boxes over the area of the smaller box. If this ratio exceeds a user-defined threshold, then the box with the lower SVDD score is suppressed. Note that this modified form of pairwise max suppression improves the interaction of two detections at nearby spatial locations but of different scales, thus lowering the number of false alarms (*11*). The pairwise suppression is performed either in an exhaustive or greedy fashion over all pairs of SVDD detections at all scales. The output of the NMS stage is a set of final detections representation the location and scale of detected humans within the input image.

4. Experimental Results

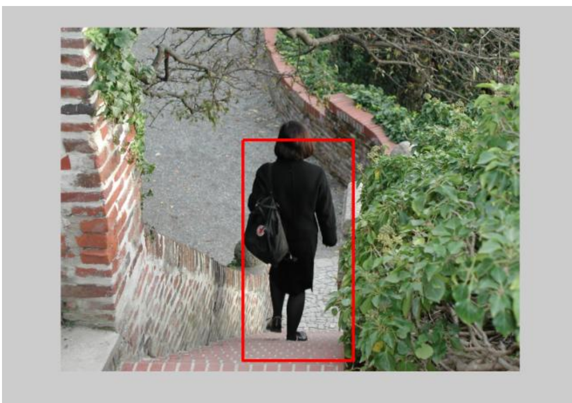
The proposed unsupervised pedestrian detection algorithm was tested on the INRIA dataset (*9*) to illustrate its performance on a benchmark dataset. The upper limit on the number of outliers or anomalies to be allowed at each scale in the experiment ν is set to 10% of the total number of data samples at that particular scale. There are very few data samples available at very small scales of the input image (corresponding to very large pedestrians in the input images) to model the enclosing hypersphere of the normalcy class. So the data samples from the smallest eight scales of each input image are grouped together before modeling the normalcy class, and then the anomalies (pedestrians) are obtained for these eight scales together.

A subset of the INRIA dataset consisting of 230 images with sizes 640×480 and 480×640 are used to test the proposed algorithm. Figure 4 shows the final bounding boxes in the images representing the pedestrian detections. As shown in this figure, the proposed algorithm is capable of detecting pedestrians in urban and rural scenes. However, the number of false alarms appears to be higher in urban scenes, as exemplified in figures 4a, d, and f. This observation is due to the fact that some of the detection windows in the urban scenes have local spatial structures that are quite different from the majority of the image. So, these windows are deemed to be anomalies along with pedestrians. At present, the detection rate of the proposed algorithm is around 54% at 1 false alarm per image. The false alarm rate will drop sharply in rural scenes with less clutter.

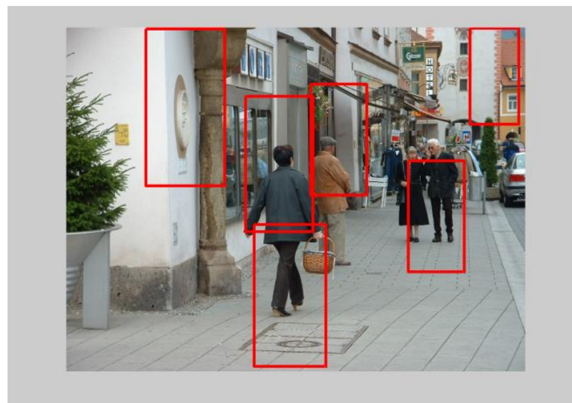


(a)

(b)

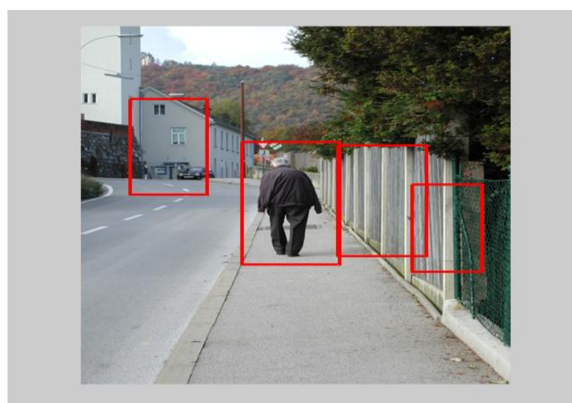


(c)



(d)

(e)



(f)

Figure 4. Pedestrian detections generated by the unsupervised pedestrian detection algorithm.

5. Conclusion

In this report, we have developed an unsupervised pedestrian detection algorithm using SVDD. The only prior information used is an average pedestrian HOG template. Using this template, a distance feature vector is extracted for each detection window and used in normalcy class modeling. By setting the upper limit on the number of outliers, the windows containing pedestrians are detected as anomalies during the modeling stage. The performance of the algorithm is demonstrated using a benchmark dataset from INRIA. Even though the algorithm generates more false alarms compared to some supervised human detection techniques, it has shown great potential in detecting pedestrians without any training sets. However, if a majority part of an input image is covered by humans, the proposed algorithm will fail because the humans are no longer outliers but becoming the normalcy class. Our future work includes reducing the number of false alarms, as well as dealing with large number of pedestrians in an image. Research work on different distance metrics to calculate the feature vectors will also be performed in the near future.

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Appendix. Code for the Unsupervised Pedestrian Detection

The following is the code for the unsupervised pedestrian detection algorithm.

```
%%%%% Program to read in images, perform UHD, and write out
%%%%% the BB of detections
%
% %

clear all;

% Reading in the data
imdir = 'C:\Users\SOAR\Documents\D2D\UHD\dset\';
files = dir([imdir '*png']);
nfiles = size(files,1);
resbbdir = 'C:\Users\SOAR\Documents\D2D\UHD\dset\BB\';
resmsdir = 'C:\Users\SOAR\Documents\D2D\UHD\dset\MS\';

% Parameters
rw = 128;
cw = 64;
margin = 3;
stride = 8;

% Loading the average human
load AvgHOGpos.mat;
avghog = AvgHOGpos;

% Perform UHD and write out the BB
for k = 1:nfiles
    fname = files(k).name;
    im = imread([imdir fname]);
    [rim,cim,zim] = size(im);
    % detection window size used during training
    Sr = 1.05;     % scale stride
    Ss = 1;    % start scale
    Se = min([(rim-2*margin)/rw (cim-2*margin)/cw]);     % end scale
    Sn = floor(log(Se/Ss)/log(Sr)+1);      % number of scale steps Sn
    %%% Vectors of scales to resize each image by
    Si = Ss*(Sr.^([1:Sn]-1));
    Si(end) = [];
    Sn = Sn-1;
    IDen = [];
    for ii=1:Sn-8
        k
        ii
        imrs = imresize(im,1/Si(ii),'bilinear');
        [HOGw_all,imtrunc,c_r,c_c,nw_r,nw_c] =
HOGfun(imrs,avghog,margin,stride,rw,cw);
        [r c] = size(c_c);
        c_r = (c_r+margin)*Si(ii);
        c_c = (c_c+margin)*Si(ii);
```

```
        r_coords = reshape(c_c',r*c,1);
        c_coords = reshape(c_r',r*c,1);
        dwinsize = [rw*Si(ii) cw*Si(ii)];
        IDnew = floor([c_coords-dwinsize(1)/2  r_coords-dwinsize(2)/2
c_coords+dwinsize(1)/2 r_coords+dwinsize(2)/2]);
        TrainData = HOGw_all;
        TrainData(HOGw_all<0) = 0;
        nu = 0.01;
        N = size(TrainData,1);
        C = 1/(nu*N);
        sigmavals = 1:1:39;
        sigma = minimaxest(TrainData,C,sigmavals);
        Labels = ones(N,1);
        Kr = exp(-sqeucldistm(TrainData,TrainData)/(sigma*sigma));
        [alf,R2,Dx,J] = svdd_optrbf_mod2(TrainData,Labels,C,Kr);
        SVx = TrainData(J,:);
        alf = alf(J);
        R1 = 1 + sum(sum((alf*alf').*exp(-
sqeucldistm(SVx,SVx)/(sigma*sigma)),2));
        Ra = R1+R2;
        I = find(alf==C);
        m = size(I,1);
        if m>0
            svx = TrainData(J(I),:);
            alfc = alf(I);
            K = exp(-sqeucldistm(svx,svx)/(sigma*sigma));
            RR = R1 - 2*sum( repmat(alfc',m,1).* K, 2);
            RR = RR/Ra;
            IDen = [IDen;IDnew(J(I),:) RR];
        end
    end
    HOGALL = [];
    IDnew = [];
    for ii=Sn-7:Sn
        k
        ii
        imrs = imresize(im,1/Si(ii),'bilinear');
        [HOGw_all,imtrunc,c_r,c_c,nw_r,nw_c] =
HOGfun(imrs,avghog,margin,stride,rw,cw);
        HOGALL = [HOGALL;HOGw_all];
        [r c] = size(c_c);
        c_r = (c_r+margin)*Si(ii);
        c_c = (c_c+margin)*Si(ii);
        r_coords = reshape(c_c',r*c,1);
        c_coords = reshape(c_r',r*c,1);
        dwinsize = [rw*Si(ii) cw*Si(ii)];
        IDnew = [IDnew;floor([c_coords-dwinsize(1)/2  r_coords-dwinsize(2)/2
c_coords+dwinsize(1)/2 r_coords+dwinsize(2)/2])];
    end
    TrainData = HOGALL;
    TrainData(HOGALL<0) = 0;
    nu = 0.01;
    N = size(TrainData,1);
    C = 1/(nu*N);
    sigmavals = 1:1:39;
    sigma = minimaxest(TrainData,C,sigmavals);
    Labels = ones(N,1);
```

```
    Kr = exp(-sqeucldistm(TrainData,TrainData)/(sigma*sigma));
    [alf,R2,Dx,J] = svdd_optrbf_mod2(TrainData,Labels,C,Kr);
    SVx = TrainData(J,:);
    alf = alf(J);
    R1 = 1 + sum(sum((alf*alf').*exp(-
sqeucldistm(SVx,SVx)/(sigma*sigma)),2));
    Ra = R1+R2;
    I = find(alf==C);
    m = size(I,1);
    if m>0
        svx = TrainData(J(I),:);
        alfc = alf(I);
        K = exp(-sqeucldistm(svx,svx)/(sigma*sigma));
        RR = R1 - 2*sum( repmat(alfc',m,1).* K, 2);
        RR = RR/Ra;
        IDen = [IDen;IDnew(J(I),:) RR];
    end
    bbs = [IDen(:,2) IDen(:,1) IDen(:,4)-IDen(:,2) IDen(:,3)-IDen(:,1)
IDen(:,5)];
    % Bounding box NMS
    bbsnm = bbNms(bbs,'type','maxg','overlap',0.2,'ovrDnm','min');
    IDennm = [bbsnm(:,2) bbsnm(:,1) bbsnm(:,2)+bbsnm(:,4)
bbsnm(:,1)+bbsnm(:,3)];
    % Mean shift NMS
    bbsms = bbNms(bbs,'type','ms','radii',[0.3 0.3 1 1]);
    bbsms(:,1:4) = round(bbsms(:,1:4));
    IDenms = [bbsms(:,2) bbsms(:,1) bbsms(:,2)+bbsms(:,4)
bbsms(:,1)+bbsms(:,3)];
    % Writing out the bounding boxes
    fname(end-3:end) = [];
    % Bounding box NMS
    fid = fopen([resbbdir fname '.txt'],'w');
    for jj = 1:size(bbsnm,1)

fprintf(fid,'%d,%d,%d,%d,%f\r\n',bbsnm(jj,1),bbsnm(jj,2),bbsnm(jj,3),bbsnm(jj
,4),bbsnm(jj,5));
    end
    fclose(fid);
    % Mean shift NMS
    fid = fopen([resmsdir fname '.txt'],'w');
    for jj = 1:size(bbsms,1)

fprintf(fid,'%d,%d,%d,%d,%f\r\n',bbsms(jj,1),bbsms(jj,2),bbsms(jj,3),bbsms(jj
,4),bbsms(jj,5));
    end
    fclose(fid);
end
```

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